Original Research Article

Dynamic modeling and motion control strategy simulation analysis of robots

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Abstract: Objective: This paper investigates the methods for robotic dynamic modeling and evaluates the performance of motion control strategies, focusing on accuracy, stability, and real-time capabilities in complex trajectory tracking. The aim is to provide theoretical support for optimizing motion control strategies. Methods: A six-degree-of-freedom robotic manipulator dynamic model is established based on the Lagrangian method. Three control strategies—PID control, sliding mode control (SMC), and model predictive control (MPC)—are implemented for simulation experiments. Their performance is compared in terms of trajectory error, torque fluctuation, and computational cost. Results: The experiments demonstrate that MPC achieves the highest trajectory accuracy (RMS error: 0.009 m) and the lowest torque fluctuation (0.14 Nm), but has a longer computation time (4.3 ms/step). Sliding mode control exhibits strong robustness with moderate computational efficiency, while PID control provides the best real-time performance but with relatively larger errors (0.018 m). Conclusion: MPC is suitable for high-precision and complex tasks, sliding mode control is appropriate for scenarios requiring strong robustness, and PID control is more suitable for industrial environments with high real-time demands. This study provides a reference for the application of dynamic modeling and control strategies.

Keywords: Robotic dynamic modeling; Motion control strategies; Trajectory tracking; Model predictive control

1. Introduction

The study of Dynamic Modeling and Motion Control Strategies for Robots stands as a crucial field in robotics research, extensively applied across manufacturing, healthcare, and service industries. Dynamic modeling forms the basis for designing control strategies and significantly influences their performance, whereas control strategies are key in determining robots' adaptability in ever-changing settings. Key modeling techniques encompass the Newton-Euler approach, known for its real-time efficiency, and the Lagrangian technique, providing structured unification. While PID control is straightforward and user-friendly, its sturdiness is restricted; while sliding mode control effectively blocks disturbances, it may lead to chattering; MPC attains precise control via dynamic optimization, yet it demands significant computational resources. This research models a robotic manipulator with six degrees of freedom utilizing the Lagrangian approach. PID, sliding mode control, and MPC are executed and evaluated via simulated experiments. Analysis of the performance takes into account trajectory inaccuracies, variations in torque, and computational expenses, offering a theoretical foundation for refining control tactics.

2. Robot dynamic modeling

2.1. Dynamic modeling methods

Robot dynamic modeling serves as the theoretical foundation for studying robot kinematics and control. The main methods include the Newton-Euler method and the Lagrangian method. The Newton-Euler method is based on rigid body mechanics and Newton's second law for recursive computation. It is suitable for scenarios with high real-time requirements but involves a complex derivation process, making it less intuitive for analyzing system energy variations[1]. The Lagrangian method constructs dynamic equations using the difference between kinetic and potential energy. It is uniform in form and has clear physical significance, making it more suitable for multi-degree-of-freedom system modeling. Each method has its advantages and limitations, and the choice depends on the complexity of the robot's motion, modeling accuracy, and real-time requirements.

2.2. Lagrangian dynamic modeling process

Dynamic modeling based on the Lagrangian method requires constructing the system's kinetic and potential energy expressions while using generalized coordinates to describe the motion states of the robot's joints. The kinetic energy is determined by the velocities and inertial properties of the robot's components and can be expressed as, whereM(q)is the inertia matrix. The potential energy is related to the system's mass distribution and position and can typically be represented asP=mgh. By substituting the kinetic and potential energies into the Lagrangian equation: the system's dynamic equations can be derived. The robot system's dynamic equations can be normalized into the standard form: whererepresents the inertia matrix,is the Coriolis torque term,is the gravitational term, andis the joint torque.

2.3. Robot dynamic characteristics analysis

Analyzing dynamic characteristics is fundamental to dynamic modeling, uncovering how inertia, Coriolis torques, and gravity influence the system's efficiency in controlling motion. The inertia matrix, characterized as a symmetric positive-definite matrix, exerts a direct impact on the system's stability in motion and its dynamic reaction. The term 'Coriolis torque' characterizes the interconnection among joint speeds, a nonlinear aspect that requires meticulous consideration in rapid motion[2]. Gravitational forces are intimately linked to the robot's stance and are crucial for sustaining a stationary position and optimizing energy usage. Such evolving traits form an essential foundation for the creation of control tactics.

3. Robot Motion control strategies

3.1. Classification of control strategies

Strategies for controlling robot motion fall into three distinct categories: traditional control, smart control, and sophisticated control. Theoretically, PID control, a form of classical control, is straightforward and simple to execute, rendering it apt for a majority of industrial uses.

3.2. Trajectory tracking control strategies

The fundamental function of tracking trajectories in robotic motion control lies in precisely adhering to set paths within changing settings. PID control modifies errors using proportional, integral, and derivative methods, providing a straightforward framework yet falling short in precision and resilience for intricate trajectories[3]. Sliding mode control (SMC) attains rapid convergence of errors through sliding surfaces, outperforming PID in rejecting disturbances, albeit potentially leading to chattering. MPC continuously fine-tunes upcoming control inputs by employing rolling optimization, adjusting to environmental shifts, and attaining precise trajectory monitoring.

3.3. Applicability analysis of control strategies

PID control, known for its minimal computational demands and apt for high-performance real-time situations, struggles with intricate trajectories and the rejection of disturbances. The use of sliding mode control ensures robustness and suitability in scenarios of nonlinear disturbances, though there's a need to fine-tune chattering problems. MPC stands out for its accuracy and adaptability, yet it faces significant computational challenges, rendering it ideal for applications demanding high precision and ample computational power[4]. The detailed examination provides a guide for choosing control techniques in real-world engineering scenarios.

4. Simulation experiment design

4.1. Experimental objectives and scenario description

This experiment's objective is to confirm the precision of robotic dynamic modeling and to assess the efficiency and resilience of various motion control tactics in intricate trajectory tracking activities. This experimental setup utilizes a six-degree-of-freedom model for robotic manipulation, establishing the path as a three-dimensional composite trajectory, including sine, cosine, and linear elements: To simulate a complex environment, random disturbance torques are applied during the experiment, with amplitudes within ±10% of the joints' maximum rated torque.

4.2. Simulation tools and experimental procedure

The experiment uses MATLAB/Simulink to construct the dynamic model, along with Robotics Toolbox for model validation. The control algorithms include PID control, sliding mode control (SMC), and model predictive control (MPC). The experimental procedure is as follows:

(1) Construct the dynamic model of the six-degree-of-freedom robotic manipulator and verify the consistency between the model and the real system.

(2) Implement the code logic for different control algorithms in the simulation environment, including trajectory error calculation, control signal generation, and feedback updates.

(3) Collect simulation data and record trajectory errors, control torques, and computational time.

4.3. Experimental design details

Creating the experimental path is accomplished using established formulas, with the target position and speed being dynamically modified throughout the simulation. A white noise generator is employed to replicate random disturbance scenarios, overlaying the control signal to imitate actual interference settings. Sampling of data occurs over a duration of 1 ms, with the assessment criteria encompassing the following:

(1) Trajectory Tracking Error (RMS): whereis the target position, andqis the actual position.

(2) Control Torque Fluctuation: Evaluated using the standard deviation of the torque:

(3) Computational Cost: Calculated by dividing the total simulation time by the number of simulation steps to obtain the average time per step.

5. Experimental results and analysis

5.1. Comparative analysis of metrics

Results from the RMS error analysis reveal MPC's superior precision in handling intricate trajectories, boasting an error rate of 0.009 m, surpassing both sliding mode control (0.012 m) and PID control (0.018 m). This indicates that MPC's dynamic optimization method provides greater accuracy in changing settings, in contrast to PID control, which suffers from more errors owing to its insufficient overall predictive power.

Variations in torque serve as a vital measure of a system's stability[5]. Findings indicate that MPC exhibits the minimal torque variation (0.14 Nm), succeeded by sliding mode control (0.18 Nm) and PID control (0.25 Nm). This indicates that MPC proficiently fine-tunes the dynamic allocation of control torques, and the use of sliding mode control lessens the chattering impacts in contrast to PID control.

Regarding processing speed, PID control outperforms others, averaging 1.2 ms per step, in contrast to sliding mode control and MPC, which take 1.6 ms and 4.3 ms, respectively. This suggests that MPC's performance in real-time is comparatively inferior, owing to its intricate optimization computations. Consequently, MPC is better suited for situations with ample computational power, whereas PID control excels in industrial settings demanding rapid, real-time efficiency.

5.2. Discussion of resultss

Experimental findings reveal the distinct benefits of every control approach. MPC, known for its exactness and minimal torque variation, is apt for intricate situations, yet it incurs greater computational expenses. The sliding mode control is highly effective in filtering out disturbances and is apt for tasks that demand substantial resilience. PID control delivers optimal performance in real-time, rendering it suitable for situations with scarce computational power and modest precision needs.

The precision of dynamic modeling forms the basis for the efficacy of control mechanisms. The use of high-precision modeling markedly improves the flexibility and steadiness of control tactics, catering to the varied needs of multiple applications.

6. Conclusion and future prospects

6.1. Research summary

The study methodically examined the use of robotic dynamic modeling and motion control techniques, performing a comparative study of these methods via simulation experiments. Regarding dynamic modeling, the Newton-Euler technique is apt for dynamic systems demanding rapid real-time efficiency, yet it requires intricate recursive calculations. For systems with a high degree of freedom, the Lagrangian approach is preferable due to its consistent nature and straightforward descriptions of energy. This research developed dynamic equations for the six-degree-of-freedom robotic manipulator using the Lagrangian approach, confirming their precision in intricate trajectories and laying the groundwork for designing control strategies.

Analyzing various control methods revealed that MPC is adept at maintaining high accuracy and minimal torque variation, rendering it apt for intricate tasks, albeit with increased computational demands. The use of sliding mode control, known for its robustness and reasonable computational expense, is apt for tasks demanding significant disturbance elimination. PID control, known for its superior real-time efficiency, is perfectly suited for streamlined industrial settings. The outcomes of the experiments offer numerical benchmarks for the selection and enhancement of robotic motion control tactics.

6.2. Future research directions

While this research has produced significant insights, multiple avenues remain for additional investigation. Regarding dynamic modeling, current techniques frequently rely on theoretical models, overlooking elements like flexible arms, joint friction, and environmental interplays. Upcoming studies may integrate adaptable dynamics, interactions among multiple systems, and the impact of external disturbances, alongside the introduction of data-centric modeling techniques to enhance the precision and usability of the model.

Regarding control tactics, the role of intelligence in development is crucial. The combination of deep learning and reinforcement learning enables the investigation of data-driven control strategy optimization models to improve the system's flexibility in unfamiliar settings. Enhancing the real-time efficiency of MPC via distributed computing will additionally boost the dependability of intricate control operations. It's essential to confirm the outcomes of simulation studies using hardware tests and broaden their applicability to collaborative systems involving multiple robots. The integration of distributed control, synchronized communication, and synchronized planning is expected to enhance both cooperation and dependability.

7. Conclusion

The research carried out experiments in dynamic modeling and motion control simulation for a robotic manipulator with six degrees of freedom, confirming the disparities in performance of different control methods in terms of trajectory tracking precision, torque fluidity, and immediate performance. Findings show MPC leads in high-precision control, sliding mode control excels in resilience and disturbance control, and PID control, though not as precise, is apt for industrial use owing to its straightforward implementation and superior real-time efficiency. This research uncovers the vital role of precise dynamic modeling in the efficacy of control strategies. Upcoming studies aim to investigate the dynamics of flexible arms, modeling based on data, and optimizing control for collaboration among multiple robots, with physical experiments to validate the real-world use of robotic technology in intricate settings.

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